Amendments to the Claims

The listing of claims will replace all prior versions, and listings, of claims in the application:

Listing of Claims:

1. Claim 1 (currently amended): A computerized method in decision system applications ~~such as data mining, automatic process control, automatic target recognition, intelligent search, and machine vision~~ for collecting global or population characteristics for decision tree regulation to achieve robust decisions in spite of the application dynamics and/or errors in training data comprises the following steps:
   (a) ~~Means~~Step for inputting an existing decision tree encapsulating the knowledge acquired from practical applications;
   (b) ~~Means~~Step for inputting a set of training samples;
   (c) ~~Means~~Step for using the decision tree and the training samples to determine and output a ~~decision~~ characteristic for at least one decision tree node, said ~~decision~~ characteristic selected from the group consisting of global characteristics and population characteristics calculating weighted global class training sample proportion of the at least one decision node;
   (d) ~~wherein~~ Step for receiving an input sample; and
   (e) Step for using the ~~decision~~ characteristic output to regulates the decision tree for making robust decisions on the input sample ~~new data~~ in decision system applications such as automatic process control, automatic target recognition and machine vision.

Claims 2 - 3 (canceled).

Claim 4 (previously presented): The method of claim 1 wherein the global characteristics include global counts calculating weighted class training sample count for samples that are up to k layers above a node.

Claim 5 (canceled).

Claim 6 (previously presented): The method of claim 1 wherein the population characteristics include local population statistic calculating weighted class training sample proportion of the at least one decision node.

Claim 7 (currently amended): A computerized method in decision system applications ~~such as data mining, automatic process control, automatic target recognition, intelligent search, and machine vision~~ for classification regulation by information integration to achieve robust decisions in spite of the application dynamics and/or errors in training data comprises the following steps:

(a) ~~Means~~Step for inputting an existing decision tree encapsulating the knowledge acquired from practical applications;

(b) ~~Means~~Step for inputting a plurality of ~~decision~~ characteristics selected from the group consisting of global characteristics and population characteristics calculating weighted global class training sample proportion from at least one terminal node of the decision tree;

(c) ~~Means~~Step for determining the confidence value for each of the plurality of said ~~decision~~ characteristics ~~wherein the confidence value is defined~~ as the ratio between characteristic value of a class and that of all classes;

(d) ~~Means~~Step for determining and outputting an integrated confidence value for each class of said at least one terminal node;

(e) ~~Wherein~~Step for receiving an input sample; and

(f) Step for integrating the confidence value using ~~integrates~~ local and consistent global information for making robust decisions on the input sample ~~new data~~

in decision system applications such as automatic process control, automatic target recognition and machine vision.

Claims 8 - 9 (cancelled).

Claim 10 (previously presented): The method of claim 7 wherein the global characteristics and population characteristics are selected from the group consisting of global counts, local counts, global population statistic, and local population statistic calculating weighted class training sample proportion of the at least one terminal node of the decision tree.

Claim 11 (previously presented): The method of claim 7 wherein the confidence value is selected from the set consisting of local count confidence, local population confidence, global count confidence and global population confidence wherein the local count confidence for class c in a terminal node n is defined as

$$LC_c^n = \frac{N_c^n}{\sum_{c \in All\_Classes\_in\_n} N_c^n}$$

the local population confidence for class c in a terminal node n is defined as

$$LP_c^n = \frac{P_c^n}{\sum_{c \in All\_Classes\_in\_n} P_c^n}$$

the global count confidence for class c in a terminal node n is defined as

$$GC_c^n = \frac{G_c^n}{\sum_{c \in All\_Classes\_in\_n} G_c^n}$$

the global population confidence for class c in a terminal node n is defined as

$$GP_c^n = \frac{g_c^n}{\sum_{c \in All\_Classes\_in\_n} g_c^n}.$$

Claim 12 (cancelled).

Claim 13 (previously presented): The method of claim 7 wherein the global characteristics have a global context coverage that is adjusted using different layer depths wherein the global context is from layers above a node determined by the different layer depths.

Claim 14 (cancelled).

Claim 15 (currently amended): A computerized method in decision system applications ~~such as data mining, automatic process control, automatic target recognition, intelligent search, and machine vision~~ for decision tree pruning regulation by information integration to achieve robust decisions in spite of the application dynamics and/or errors in training data comprises the following steps:

(a) ~~Means~~Step for inputting an existing decision tree encapsulating the knowledge acquired from practical applications;

(b) ~~Means~~Step for inputting a set of training samples;

(c) ~~Means~~Step for generating a regulated measure using the decision tree and the training samples selected from the group consisting of integrated confidence values and reliability measures comparing local, global, count and population confidences;

(d) ~~For a non-terminal node of the tree having two descending terminal nodes, Means~~Step for determining the accuracy values for a non-terminal node of the decision tree having two descending terminal nodes using the regulated measure under two separate nodes or combined node conditions;

(e) ~~If combined node accuracy value is greater than the two separate node accuracy value,~~ Step for pruninge the terminal nodes by combing the two terminal nodes and converting the associated non-terminal nodes into one

terminal node if combined node accuracy value is greater than the two separate node accuracy value; ~~wherein~~ and

(f) Step for outputting a simplified decision ~~pruned~~ tree for avoiding over-fitting of data allowing robust decisions on new data in decision system applications such as automatic process control, automatic target recognition and machine vision.

Claim 16 (previously presented): The method of claim 15 wherein the reliability measures include a local population reliability measure $R_{l,P}$ defined as

$$R_{l,P} = 1 - 2 * \left| \frac{LP_c^n}{(LC_c^n + LP_c^n)} - 0.5 \right|.$$

Claim 17 (previously presented): The method of claim 15 wherein the reliability measures include a count reliability measure R_c defined as

$$R_c = 1 - 2 * \left| \frac{GC_c^n}{(LC_c^n + GC_c^n)} - 0.5 \right|.$$

Claim 18 (previously presented): The method of claim 15 wherein the reliability measures include a population reliability measure R_P defined as

$$R_P = 1 - 2 * \left| \frac{GP_c^n}{(LP_c^n + GP_c^n)} - 0.5 \right|.$$

Claim 19 (cancelled).

Claim 20 (previously presented): The method of claim 15 wherein the reliability measures include a global population reliability measure R_{GP} defined as

$$R_{GP} = 1 - 2 * \left| \frac{GP_c^n}{(GC_c^n + GP_c^n)} - 0.5 \right|.$$

Claims 21 - 22 (canceled).

Claim 23 (currently amended): A computerized method in decision system applications ~~such as data mining, automatic process control, automatic target recognition, intelligent search, and machine vision~~ for decision tree generation regulation by information integration to achieve robust decisions in spite of the application dynamics and/or errors in training data comprises the following steps:

(a) ~~Means~~Step for inputting a set of training samples acquired from practical applications;

(b) ~~For at least one node, means~~Step for generating set of candidate thresholds for at least one node;

(c) ~~Means~~Step for partitioning data at a candidate threshold;

(d) ~~Means~~Step for calculating an evaluation function selected from the set consisting of integrated confidence value and reliability measures comparing local, global, count and population confidences;

(e) Repeat steps (c) and (d) for a plurality of partitions and select the partition for the node as the one that maximizes the evaluation function;

(f) ~~wherein~~Step for outputs a highly robust decision tree classifier using the partition for the node;

(g) allows Step for receiving an input sample; and

(h) Step for using the highly robust decision tree classifier for robust decisions on the input sample ~~new data~~ in decision system applications such as automatic process control, automatic target recognition and machine vision.